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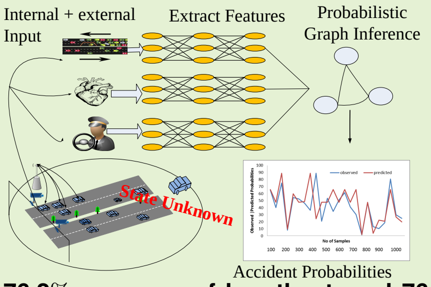
# A Human-in-the-Loop Probabilistic CNN-Fuzzy Logic Framework for Accident Prediction in Vehicular Networks

Muhammad Usman, Anil Carie, Bhaskar Marapelli, Hayat Dino Bedru, and Kamanashish Biswas

***Abstract*—The vehicle accident prediction methods are designed to improve the vehicular safety and reduce the rescue response time in the case of an accident. The existing accident prediction methods, however, do not involve Human-in-the-Loop, i.e., do not consider the emotional state of a driver to predict the likelihood of an accident. We propose a Probabilistic Convolutional Neural Network (CNN)-Fuzzy Logic framework that involves Human-in-the-Loop and takes into account the multiple input streams of sensor generated data, i.e., human emotions and traffic data. The features extracted from the CNN model are fed to our designed probabilistic graph-based inference model to determine the accident probability. The probability is then mapped with accident severity through fuzzy membership functions for accident prediction. The experiment results show the promising performance of our proposed framework, i.e., 93.1% accuracy of face expressions, 76.2% accuracy of heartbeat, and 76.9% accuracy of traffic inputs and predicts the accident likelihood with 90% accuracy. The comparison, with related works, shows that the proposed framework can predict accidents with higher probabilities.***



***Index Terms*—Accident Prediction; Convolution Neural Network; Deep Learning; Fuzzy Logic; Human-in-the-Loop.**

## I. Introduction

RECENT advancements in sensing and actuating technology, along with the developments of innovative intelligent solutions, have realized the realm of Intelligent Transportation System (ITS) [1]–[3]. ITS has a number of input streams of data coming through various sources such as traffic control systems, vehicular sensors, and driver-generated data to offer next-generation vehicular services such as maintaining traffic efficiency, offering safety and comfort to drivers and passengers, fleet management, and many others [4]. Vehicular safety against accidents is an imperative aspect that must be considered while designing any ITS service. According to World Health Organization, a large proportion of deaths and injuries all over the world are due to road accidents [5]. In many cases, the deaths are due to lack of coordination with the vehicles or lack of timely alerts generated by the coordinated systems for vehicles. Thus, there is a need for a robust accident alerting framework for improving the road safety by taking into account different streams of data.

The underlying sensors, however, may generate imprecise values in cyber-physical systems in general, and ITS, in particular, along with inherited randomness involved in the transportation data [6]–[8]. The researchers from academia and industry has explored deep learning, graph theory, fuzzy logic, and other soft computing domains to design different safety solutions in vehicular networks [9]–[12].

The existing deep learning-based works have primarily focused on the accident detection and recovery by mainly considering traffic flow, travel time estimation, and predicting modes of transport [9], [10]. Probabilistic graph models are used for analyzing the hidden relationships between the various elements in unstructured data [10]. The graph based representation is used for encoding and factorizing representation of independence in distribution space. Similarly, the probabilistic and fuzzy logic-based models are studied to solve the vehicle-centric safety problem [11], [12]. Most of these existing solutions, however, mainly consider external information (i.e., traffic status, vehicle speed, etc.,). The internal emotional state of the driver is not considered in these studies. The automatic prediction of emotion promises to revolutionise human-computer interaction; thus, offering more reliable services in realms such as ITS. Recent trends involve fusion of multiple data modalities - audio, visual, and physiological - to predict

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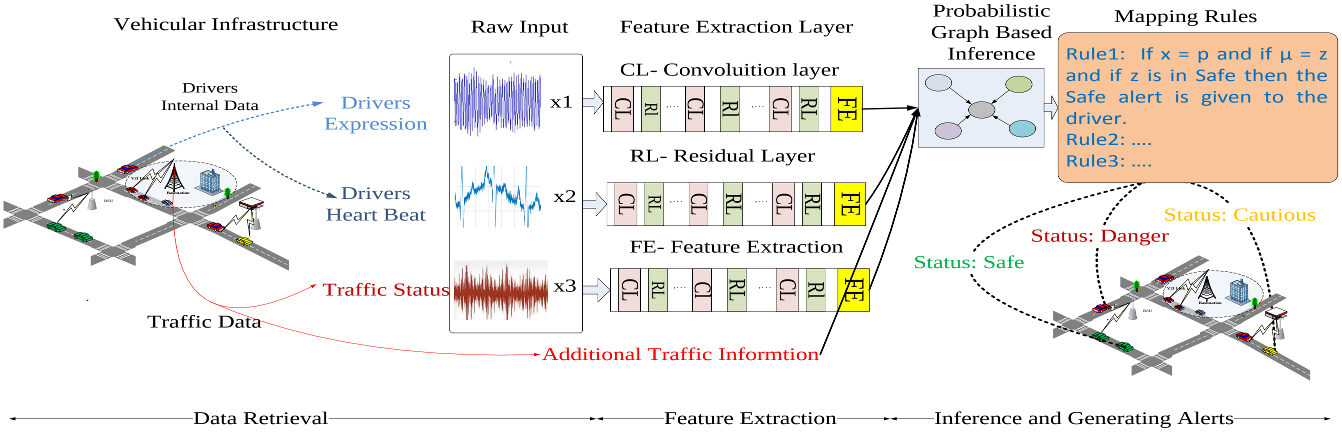

Fig. 1: Accident prediction framework

emotional state [13]. The accurate prediction of emotions of drivers may play significant role in avoiding traffic accidents.

To bridge the above-cited research gaps, this study aimed at designing and analyzing a probabilistic convolutional Neural Network (CNN)-Fyzz Logic framework to effectively predict accidents using both external and internal parameters. The fuzzy logic embodies the degree to which outcome of the graph-based inference model is associated with driver alerts. As a first step, we used Kaggle's facial expression, heartbeat, and traffic data set. Then we use CNN model to classify emotion, abnormal heartbeat, and traffic situation. This is followed by designing a probabilistic graph-based inference model to predict the accident probability by extracting complex relationships between drivers internal information and external traffic information for inference. Finally, the accident probability is mapped to accident severity to generate alerts to the driver. The experiments show the promising results of our proposed framework. The key novelties of our proposed framework are summarized below:

1) We designed a deep learning-based model that considers both internal state of the driver and external states of vehicle and traffic for accident prediction. The internal state is determined through facial expressions and heartbeat status of drivers. The external states are determined through vehicular and traffic data parameters.
2) The output of above model is fed to our proposed probabilistic graph-based inference model to determine the accident probabilities.
3) Finally, we defined fuzzy logic-based rule base mapping to map accident probability to severity of the accidents to generate alerts to drivers.

The rest of the paper is structured as follows: Section II elucidates the related work. The proposed framework is described in Section III. Performance of the presented framework is evaluated in Section IV. Section V concludes the findings of this work.

## II. Related Work

Li *et al.* [14] proposed an accident prediction model by exploiting multi-dimensional time series information. The grey correlation was studied to assess the influence of time series of each factor-variable on each accident causing variable. The closeness centrality measure was computed to measure the degree of correlation amongst the factor and accident variables. Zheng *et al.* [15] proposed a hybrid deep learning-based model, Conv-LSTM, to predict traffic flows, based on CNN and the long short-term memory network. The model extracts the intrinsic characteristics of the data of traffic flows and mines the spatio-temporal characteristics of traffic flow. Wu *et al.* [16] proposed a similar model by using CNN to extract the spatial characteristics of traffic flow and designed LSTM for extracting the dynamic characteristics of traffic flows.

A Markov model was presented to predict accidents based on spatial and temporal distribution characteristic of accidents [17]. The correlations between road type, traffic flow, and traffic accident were derived. The network latency measurement was estimated using multimodel deep learning for the selection of a server [18]. The authors studied the impact of driver stress and fatigue in car accidents [19]. This indicates the lack of multimodel techniques in this research domain.

The existing models, however, do not consider the emotional state of drives. Most of the previous works considered passive vehicle dynamics such as air bag, automatic breaking system, and inter-vehicle distance that have improved safety to a certain degree. Another research dimension has explored the possibility of designing algorithms considering real time parameters such as traffic status, vehicle speed, etc., [21]. However, the primary limitation of the current deep learning models is non-consideration of emotional state of drivers. Research shows human error plays a significant role in car accidents. Particularly, by novice drivers in the complex road environments [20]. Thus, designing a method that takes into account the emotional state of drivers and road traffic is desired to timely generate alerts to prevent car crashes.

TABLE I: Notations

| Symbol | Description | Symbol | Description |
|---|---|---|---|
| $e_s$ | smile | $t_h$ | high traffic |
| $e_n$ | neutral | $P(A)$ or $PA$ | accident probability |
| $e_a$ | angry | FI | Facial Images |
| $h_n$ | normal heartbeat | HB | Heartbeat |
| $h_a$ | abnormal heartbeat | TF | Traffic Flow |
| $t_l$ | low traffic | D | input data |
| $t_m$ | medium traffic | O | observed evidences |

## III. Proposed Framework

The accident prediction framework has a number of phases, namely, data retrieval, features extraction, probabilistic graph-based inference modeling, mapping rules, and generating results, as shown in Fig. 1. The key notations are given in Table I.

### A. Accident Prediction Method

*1) Features Extraction:* The CNN model is formulated for features extraction [30]. The input data to the CNN model is emotion data of drivers (also called drivers internal data in this case) and external traffic information. These features are given as input to the inference model to derive meaningful conclusions. There are two layers of the CNN model: forward and backward transmission. In forward transmission, internal and external information are passed as input to the convolution layers and output is obtained. In general, there are $n$ input matrices, $x_i$ represents the $i^{th}$ input matrix, and $c_i$ represents the $i^{th}$ sub-convolution matrix. Equation (1) shows the convolution block in CNN [30].

$$y^{conv}_{w,b}(x) = f(W^T x) = f(\sum_{i=1}^{n} w_i x_c + b) \tag{1}$$

where $W^T$ is the matrix in convolution layer, $x$ and $y^{conv}_{w,b}(x)$ are the input and output of the convolution layer, respectively. The notation $b$ is the deviation and $f$ is the activation function.

The residual function used to solve the saturation problem in the activation function is given by (2) [30].

$$y^i_{resi} = x^{i-1} + \delta(x^{i-1}, \theta^{i-1}) \tag{2}$$

where $x^{i-1}$ and $y^i_{resi}$ are the current input and output, respectively. The error between output and actual values is computed.

*2) Input Data Description:* The input data is derived from driver's facial expressions, heartbeat, and traffic status.

$$x_{type} : x_{expression}, x_{heartbeat}, x_{traffic-flow} \tag{3}$$

In the CNN model, small changes in the input can cause disruption in the output. To address this issue, the activation function is used. The activation function, $f$, has the saturation problem. To solve the saturation problem, the residual function is used. The complete CNN model is defined as given below

$$x^i = x^{i-1} + \delta(x^{i-1}, \theta^{i-1}) \tag{4}$$

where $i$ represents layer, $\delta$ is error function, and $\theta$ is the parameter related to the previous layers. The model gets better using the learning parameters and reduces the error.

$$L(\theta) = \| - Y_t - Y'_t\|^2 \tag{5}$$

*3) Algorithm:* The data is generated by the cooperative vehicular infrastructure. The internal (emotional) driver and the external vehicular network data is derived. Both data streams are then fed to the Algorithm 1 CNN model to train it until the optimal parameters are achieved. Then predictions from the test data are derived. The CNN model gives outputs, namely, driver expressions: $e_s$ denotes smile, $e_n$ denotes neutral, and $e_a$ denotes angry. The driver heartbeat: $h_n$ denotes normal and $h_a$ denotes abnormal. Finally, the traffic status: $t_l$ denotes low traffic, $t_m$ denotes medium traffic, and $t_h$ denotes high traffic. These are given as input to Algorithm 2, which returns conditional probabilities of all input features from these probabilities. The accident probability $P(A)$ is then inferred and mapped to the accident severity value. The inferred $P(A)$ is then mapped to accident severity with the membership functions using (6) t (8). Finally, the alerts are generated to alert drive of any danger. The algorithmic description of the complete accident prediction process is provided in Algorithm 1.

**Algorithm 1** Accident prediction based on internal and external data

```
Input: Facial Images (FI), Heartbeat (HB), Traffic Flow (TF)
Output: Alerts
For all $x_i \in i[1,t]$ time series Do
    Construct input data using (3)
    Store $D \leftarrow FI, HB, TF$
End For
Repeat
    Select randomly $D_i \in D$
    Execute CNN using (1) and (2)
    Minimize error $\theta$ using (5)
Stop at stopping criteria
$P(O|Pa(O))$= Alg 2$(e_s, e_n, e_a, h_n, h_a, t_l, t_h, t_m, s)$
Return P(A).
Mapping $Safe, Cautious, Danger \leftarrow P(A)$
Return Alerts
```

### B. Accident Inference Model

*1) Model Description:* Fig. 2 shows the graphical representation of the extracted features, where nodes in the graph represent features and edges represent the dependent probabilities between features. This model infers the possibility of accidents based on the internal and external features in the vehicular environment. The internal features include driver expressions: $e_s$ denotes smile, $e_n$ denotes neutral, and $e_a$ denotes angry. The driver heartbeat: $h_n$ denotes normal and $h_a$ denotes abnormal. Finally, the traffic status: $t_l$ denotes low traffic, $t_m$ denotes medium traffic, and $t_h$ denotes high traffic. The algorithmic description is shown in Algorithm 2.

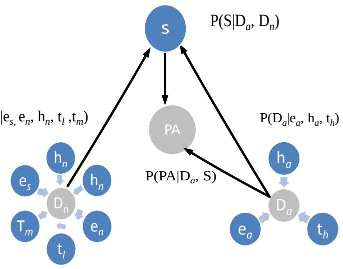

Fig. 2: Graph-based accident inference model

*2) Accident Inference:* We infer the probability of the accident ($PA$) from the outcomes of the CNN model by using them as input to the graph-based prediction model. We find $PA$ as an outcome from the model which has three categories or alerts: safe, cautious, and danger. The inference model is employed to find values of hidden nodes $(D_n, D_a, PA)$ for each instance of the CNN outcomes. After executing the algorithm, we choose max($PA$) as the inferred category. We map $PA$ into severity of accidents, and based on the membership functions, the driver will be given alerts as safe, cautious, or danger. Table II shows the relationship between $PA$, range of variables, and corresponding linguistic variables.

**Algorithm 2** Graph-based accident inference algorithm

```
Input: CNN outputs, Observed evidences
Output: Conditional probability $P(O|Pa(O))$ of each node
    Randomly initialize $P(O|Pa(O))$
    For each node O
    While $P(O|Pa(O))$ does not converge
    For Each evidence $e = (e_s, e_n, e_a, h_n, h_a, t_l, t_h, t_m, s) \in E$
    For Each value of $h = (D_n, D_a, AP) \in H$
    $P(h, e) < -P(D_n|e_n, t_l, e_s, h_n)P(D_a|e_a, t_h, t_m, n_a)$
    $\times P(AP|D_n, D_a, S)$
    For Each value of $h = (D_n, D_a, AP) \in H$
    $P(h|e) < -P(h, e)\|\Sigma_h \in HP(h, e)$
    End For
    End For
    End For
    End While
    End For
    For Each node O
    $\gamma < -$ the occurrence of $(O, Pa(O))$
    $P(O|Pa(O) < -\gamma \parallel$ the occurrence of $Pa(O)$
    End For
    Return $P(O|Pa(O))$
```

*3) Membership Function:* Accident alert severity groups are shown as fuzzy numbers and associated membership functions: "Safe", "Cautious", and "Danger. In this setting, the severity group "Safe" has a probability of accidents from 0 to 0.37 with lower limit a = 0, support limit b = 0.23, and an upper limit c = 0.37. The severity group "Cautious" has probabilities lower limit b = 0.23, a lower support limit c = 0.37, an upper support limit d = 0.53, and an upper limit e = 0.67. The severity group "Danger" has probabilities lower limit d = 0.53, support limit e = 0.67, and an upper limit f = 1. The membership in the severity group "Safe" descends gradually from accident probabilities 0.23 to 0.37. The solid lines show the fuzzy membership functions for each group. The dashed lines denote how "Safe" values can be made into non-fuzzy crisp values.

TABLE II: Accident probability illustrated as fuzzy numbers

| Probability | Range | Linguistic Variables |
|---|---|---|
| Probability of Accident P(A) | $P(A) \leq 0.37$<br>$P(A) > 0.23$ and $P(A) \leq 0.67$<br>$P(A) > 0.53$ | Safe<br>Cautious<br>Danger |

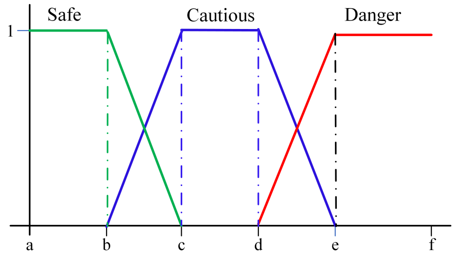

Fig. 3: Membership function

The description of vagueness in the accident severity groups, i.e., a lower limit, an upper limit, a lower support limit, and an upper support limit, can be best modeled with trapezoidal function. Based on the probability of the accident, the accident severity group "Safe" is defined as a special case of the Trapezoidal function called R−function with parameters: lower limit a = 0, support limit b = 0.23, and upper limit c = 0.37, where $a < b < c$. The "Cautious" group is defined as a Trapezoidal function with probabilities: lower limit b = 0.23, a lower support limit c = 0.37, an upper support limit d = 0.53, and an upper limit e = 0.67, where $b < c < d < e$. Finally, "Danger" is defined as another special case of the Trapezoidal function called F-function with parameters lower limit d = 0.53, support limit e = 0.67, and an upper limit f = 1, where $d < e < f$. Fig. 3 shows the membership functions of "Safe", "Cautious", and "Danger".

Let us consider the accident probability as Universe of Discourse, representing severity of accidents as three groups: "Safe", "Cautious", and "Danger". The corresponding membership functions are defined below.

For safe, if $x > c$, the corresponding function value is zero. If $b \leq x \leq c$, then the corresponding value is calculated using equation of line segment $\frac{d-x}{d-b}$. Finally, if $x < b$ the corresponding function value is 1. The function for safe is as follows.

$$\mu_{Safe}(X) = \begin{cases} 0, & x > c \\ \frac{d-x}{d-b}, & b \leq x \leq c \\ 1, & x < b \end{cases} \quad (6)$$

For cautious, if $x \leq b$, the corresponding function value is zero. If $b \leq x \leq c$, then the corresponding value is calculated using the equation of the line segment joining the two points b and c. We get $\frac{x-b}{c-b}$. For $c \leq x \leq d$, the corresponding function value is 1. For $d \leq x \leq e$, the function is again the line segment between points d and e. We get $\frac{e-x}{e-d}$. Finally, for $x \geq e$, the function value is zero. The function for Cautious is as follows.

$$\mu_{Caution}(X) = \begin{cases} 0, & (x \leq b) \ or \ (x \geq e) \\ \frac{x-b}{c-b}, & b \leq x \leq c \\ 1, & c \leq x \leq d \\ \frac{e-x}{e-d}, & d \leq x \leq e \end{cases} \tag{7}$$

For "Danger", if $x < d$, the corresponding function value is zero. If the $d \leq x \leq e$, then the corresponding value is computed using equation of the line segment joining two points d and e. We get $\frac{x-d}{e-d}$. Finally, if $x \geq e$ the corresponding function value is 1. The function for danger is as follows.

$$\mu_{Danger}(X) = \begin{cases} 0, & x \leq d \\ \frac{x-d}{e-d}, & d \leq x \leq e \\ 1, & x \geq e \end{cases} \tag{8}$$

Each group in the severity of accidents, i.e., "Safe", "Cautious", and "Danger" have a crisp membership value function. Once the max($PA$) has been inferred from the probability inference model, this probability is then mapped to related severity of accidents member. If PA falls in the region "Safe", then driver gets a safe indication. If it falls in "Cautious" region, then the driver gets cautious indication. If it falls in the region "Danger", then the driver gets Danger indication so that the driver will take appropriate measures to avoid any accident.

The detailed description is provided below:

1) Initialization of the parameters for the CNN model. The connection weights and deviation values are initialized.
2) The extraction of three types of information. We use three types of information as input: face expression (type1), heartbeat (type2), and traffic status (type3), as shown in (3).
3) The CNN model consists of a series of consecutive convolution and residual blocks.
   a) The convolution block, an activation function, is utilized to consider the non-linear factor.
   b) The residual block solved the problem of gradient dissipation caused by the inability to update the saturation network weight.

$$\delta(x, \theta) = W_2\sigma(W_1x + b_1) + b_2 \tag{9}$$

   where $W_1, W_2$ and $b_1, b_2$ are the weights and the deviations, respectively. The notation $\sigma$ is the nonlinear activation function.
4) CNN is trained by back propagating loss and Gradient decent value until the stop criteria is attained.
5) The reverse fine-tuning is performed.
   a) The loss function is calculated using (5).
   b) The stochastic gradient decent value gives loss at each layer between input and output. This is calculated using the following equation [31]

TABLE III: Performance with different datasets

| | CNN - Emotion Data | | CNN - Heart-Beat Data | | CNN- Traffic Status Data | |
|---|---|---|---|---|---|---|
| | Train | Test | Train | Test | Train | Test |
| Accuracy | 94.4% | 93.1% | 76.6% | 76.2% | 94.2% | 76.9% |
| Sensitivity | 79.0% | 81.1% | 83.0% | 87.2% | 79.1% | 83.8% |
| Precision | 31.0% | 21.1% | 19.0% | 19.2% | 29.8% | 19.2% |
| F1 score | 44.7% | 33.8% | 31.3% | 31.8% | 43.5% | 31.6% |

$$g(\theta_{ij}^{l}) = \frac{\partial L}{\partial \theta_{ij}^{l}} = \frac{\partial L}{\partial y_{ij}^{l+1}} \frac{\partial y_{ij}^{l+1}}{\partial x_{ij}^{l+1}} \frac{\partial x_{ij}^{l+1}}{\partial \theta_{ij}^{l}} \tag{10}$$

   where $\theta$ includes $w$ and $b$, $L$ is the loss function, $l$ and $l+1$ correspond to the current and next layers, $x_{ij}$ and $y_{ij}$ represent input and output.
   c) Then update the weights by back the propagating error [31]

$$\theta_{ij}^{l} = \theta_{ij}^{l} - \eta g(\theta_{ij}^{l}) = \theta_{ij}^{l} - \eta \frac{\partial l}{\partial \theta_{ij}^{l}} \tag{11}$$

   where $\eta$ is the learning rate, set to 0.0002.
6) Train the CNN model until the early stopping strategy is achieved.
7) Test using the trained optimal CNN model.
8) Graph-based inference is derived using Algorithm 2. The graph is constructed to find the hidden nodes $D_n, D_a$, and $P(A)$ from the outcomes of the CNN model. The conditional probability of each node is initialized with zeros and the EM algorithm is applied until the probability of the hidden nodes is converged. The outcome we consider here is max($P(A)$).
9) The accident probabilities are assigned memberships in three groups "Safe", "Cautious", and "Danger".
10) The max($P(A)$) inferred from graph-based inference method is mapped into "Safe", "Cautious" and "Danger" groups:
   a) If $x = p$ and if $\mu = z$ and if $z$ is in Safe then the Safe alert is given to the driver.
   b) If $x = p$ and if $\mu = z$ and if $z$ is in Cautious then Caution alert is given to the driver.
   c) If $x = p$ and if $\mu = z$ and if $z$ is in Danger then Danger alert is given to the driver, where notation $x$ is inferred probability, $p$ is inferred probability value, $\mu$ is membership of inferred probability, and $z$ is the membership value of inferred probability.
11) Using the above rule set the membership of the probability is mapped to the severity group, the groups "Safe", "Cautious", or "Danger", whichever is found, the corresponding alert is issued to the driver.
    If the mapped severity group is "Safe", then the driver will have an indication to continue with driving. If the mapped severity group is "Cautious", then the driver will have an indication to slow down the vehicle. Finally, if the mapped severity group is "Danger", then the driver will have an indication to stop the vehicle to avoid an accident.

TABLE IV: Test data with various ranges of accident prediction

| S.No | Observed | Predicted | Absolute error |
|---|---|---|---|
| ... | ... | ... | ... |
| 67 | 40.23 | 47.7 | 7.47 |
| 68 | 75.025 | 89 | 13.975 |
| 69 | 8.16 | 9.6 | 1.44 |
| ... | ... | ... | ... |
| 83 | 47.25 | 47.7 | 0.45 |
| 84 | 13.32 | 3.6 | 9.72 |
| 85 | 10.29 | 22.5 | 12.21 |
| 86 | 18.57 | 20.7 | 2.13 |
| 87 | 80.55 | 65.7 | 14.85 |
| 88 | 30.06 | 26.7 | 3.36 |
| 89 | 25.05 | 19.8 | 5.25 |
| ... | ... | ... | ... |
| 96 | 10.29 | 9.6 | 0.69 |
| 97 | 1.05 | 1.8 | 0.75 |
| 98 | 19.5 | 21.6 | 2.1 |
| 99 | 4.86 | 4.5 | 0.36 |
| 100 | 7.08 | 9.6 | 2.52 |
| ... | ... | ... | ... |
| 114 | 36.81 | 36.6 | 0.21 |
| 115 | 61.44 | 47.7 | 13.74 |
| 116 | 30.93 | 21.6 | 9.33 |
| 117 | 3.84 | 0 | 3.84 |
| 118 | 14.46 | 20.7 | 6.24 |
| 119 | 17.31 | 0 | 17.31 |
| ... | ... | ... | ... |

## IV. Performance Evaluation

### A. Experiment Setup

*1) Datasets:* We have used three datasets: emotion, heartbeat, and traffic datasets from the Kaggle website [22]. These three datasets are given as the input to the CNN (see Fig. 1). The emotion dataset contains 35,800 gray scale pictures, where each image belongs to one of the following categories: “angry”, “happy”, and “neutral”. The heartbeat dataset is taken from the PTB diagnostic ECG database which is pre-processed by Kaggle [22]. It contains 14,552 samples, which belong to the normal and abnormal categories. For traffic information, we used the PeMS dataset prepocessed by Kaggle [22]. the PeMS dataset is the widely used dataset for traffic prediction [23], where data belong to three categories: “high”, “medium”, and “low”.

### B. Performance Metrics

To evaluate the performance of the formulated CNN models, we have used the standard performance measures, namely, Accuracy, Sensitivity, Precision, and F1 score [24].

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \tag{12}$$

$$Sensitivity = \frac{TP}{TP+FN} \tag{13}$$

$$Precision = \frac{TP}{TP+FP} \tag{14}$$

$$F1 = 2\frac{sensitivity \times precision}{s}ensitivity + precision \tag{15}$$

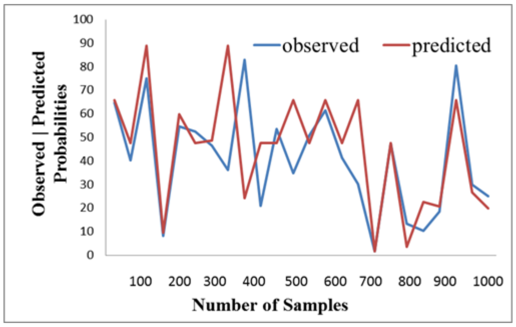

Fig. 4: Training phase: the predicted and observed accident probabilities

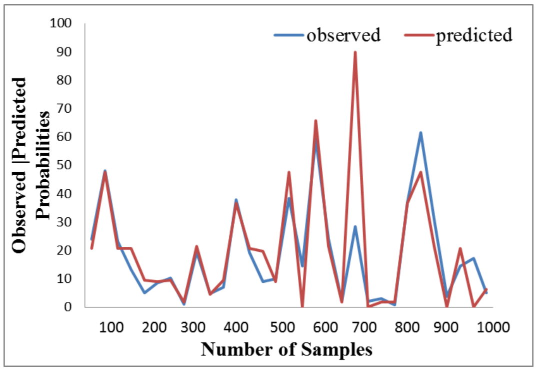

Fig. 5: Testing phase: the predicted and observed accident probabilities

### C. Results and Analysis

The proposed framework was run with the three datasets: (i) emotion dataset, (ii) traffic dataset, and (iii) heartbeat dataset. These three datasets were split into training and testing sets. The model that was built using the training data was then fed by the testing data to evaluate the overall performance of the model. The performance of the CNN model was evaluated based on the above-cited metrics.

Table III describes the performance of the CNN model before and after training. The results show the model tend to perform better with 93.1% accuracy by emotion dataset followed by 76.9% accuracy by the traffic dataset, and 76.2% accuracy by the heartbeat dataset. The probabilistic graph-based model predicts probabilities and these probabilities are compared with the observed probabilities to find the error caused by the proposed framework. Table IV shows the observed and predicted probabilities, and associated computed error. Fig. 4 and Fig. 5 provide graphical views of the differences between the probabilities for training and test data samples. The proposed framework predicted accident probabilities that are mapped to severity of accidents which will in turn generate a corresponding alert to the driver.

We have compared the predictions of our proposed framework with two models: model1 [25] and model2 [26]. Fig. 6 shows the comparative prediction probabilities. The graph shows that our framework tends to perform better as compared to the other models. This is due to the involvement of human emotions in the whole process. The deep learning models

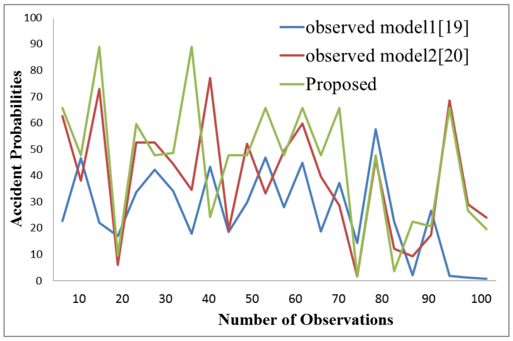

Fig. 6: Accident comparison of different models

are more dependent on the datasets and these datasets can be unbalanced leading to lack of applicability in critical domains (i.e., medical, etc) [32]–[34]. Adding probabilistic considerations to the deep learning models improves the applicability of effective computing in environments particularly when considering human emotions for decision making. In the previous models, the accident prediction is based on vehicle external information, i.e., traffic status, but in our model we have included the vehicle internal status by considering driver's emotion with face expressions and driver's heartbeat. If this internal status of the driver is abnormal, then the chance of accident is more. Hence, there are high peaks of the green line in Fig. 6. We have used a probabilistic decision making method, i.e., graph-based inference method that takes both vehicle internal and external status, and identifies probability of accidents. Since our model is based on both internal and external information with probabilistic decision making, the results vary with other models (i.e., model1 and model2).

In a previous work [27], a single dataset was used for traffic analysis and modeling. In our framework, we used three datasets which reflect better results in determining accident probability. Some other previous works used multiple datasets, but they did not consider the internal information of vehicles such as driver emotions: heartbeat and facial expression that could affect on the state of the vehicle and can cause accident [28], [29]. This shows that the driver situation has more probabilistic affect on accidents. Thus, more accurate prediction of accidents and generation of appropriate alerts can reduce the number of accidents.

Our proposed framework predicts the probability of accidents based on both internal and external information of vehicles. The external information is limited to the status of traffic, i.e., heavy or low traffic situation. It does not consider the status of other drivers in the nearby vehicles. If, in case, the internal situation of the neighboring vehicle's driver is abnormal, even though our proposed framework will give a safe alert, there may be a chance of an accident. In our future work, we intend to integrate the nearby vehicles' internal information so that our framework can make more accurate predictions of accidents.

## V. Conclusion

A probabilistic CNN-fuzzy logic framework for accident prediction in vehicular networks is proposed in this study. The proposed framework involves human-in-the-loop to classify emotions of driver, i.e., heartbeat and facial expressions in addition to considering traffic status. The proposed framework develops a probabilistic graph-based inference model to identify the probability of accident by using the classified data of the initial learning phase. Thereafter, the model maps the degree of severity of the accident by using fuzzy rule-base mapping method. Finally, the alerts are generated for the driver to take the necessary precautions. We have validated the framework on the Kaggle data, which is suitable for accident prediction having emotional state and road traffic data. The findings of the experiments show that the proposed framework outperforms the baseline methods in effectively predicting accidents by considering human-in-the-loop in addition to other important factors. The proposed framework shows better performance than the baseline methods in terms of accuracy, precision, and F1 score. We intend to design and analyze fusion operators in the current settings as part of the future work of this study.

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